Applying Zernike Moments for automatic mass diagnosis

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Purpose

The diagnosis of masses is a challenging task. In fact, it is reported that less than 30% of all breast biopsies show a malignant pathology [Barlow04]. Aiming to improve this diagnosis, different computer-aided approaches have been proposed to assist radiologists in this discrimination of benign and malignant lesions [Elter09]. These approaches are usually structured in three main steps: segmentation of the region of interest (ROI), characterisation of the segmented masses, and a posterior classification.

As an attempt to imitate the radiologists behaviour, computer-aided approaches describe masses in terms of shape, margin characteristics, optical density, and other associated findings (i.e. architectural distortion, X-ray attenuation, or location). In this paper we analyse the feasibility of describing the mass shape in terms of the Zernike moments and its potential application for the automatic mass diagnosis.

Materials and methods

In this work we used a set of 57 ROIs extracted from the MIAS mammographic database (which is the overall number of diagnosed masses: 37 were benign masses, while the rest were cancerous ones). From the annotations of the database, the ROIs were constructed using the mass centre and the mass radius multiplied by a factor of 1.25. Therefore, all the ROIs contained the mass in the centre and a small portion of normal tissue, which is useful for the segmentation step.

As mentioned before, the first step for a typical mass diagnosis system is the segmentation of the ROI. We use here the active contour approach of Chan and Vese [Chan01] which relies on the internal homogeneity in terms of grey-level of the segmented region, instead of using gradient information. The advantage of this active contour approach over the traditional gradient-based methods is that subtle masses without strong gradients can also be segmented.

Once the mass is segmented we describe its shape by using the Zernike moments [Khotanzad90]. Zernike moments are a set of descriptors obtained using complex kernel functions based on Zernike polynomials. Their main characteristics are the ability to describe a shape with minimum information redundancy (due to their orthogonality property), the robustness in noisy environments, and the fact that these moments are invariant to an arbitrary rotation of the describing shape. Zernike moments have been previously used as object descriptors in several pattern recognition and image retrieval applications with significant results.

Finally, the mass classification is performed using a Radial Basis Function Neural Network (RBF). In particular, we used in this paper a RBF network composed by three layers. The input layer is made up of source nodes that connect the network to its environment. The second layer is the only hidden layer in the network, and is used for applying a nonlinear transformation from the input space to the hidden space. The output layer is linear, supplying the response of the network to the pattern applied to the input layer. This kind of neural networks has provided satisfactory results in many pattern classification problems.

In order to perform the evaluation of our experiments we used a 10-folder cross-validation methodology. The ROI dataset was divided in 10 different groups, nine of them were merged for training the RBF and obtaining the best parameters for such group, while the remaining group was used to test the algorithms using the obtained parameters. This procedure was repeated until all groups were used for testing. Note, that using this methodology, each ROI appears in the test set only once.

Results

In order to obtain the best possible results using the Zernike moments we applied an extensive search computing all the possible moment combinations from order 0 to order 12. The best results were obtained when using the moments of order 1, 3, 6, 8, 11, and 12, with the confusion matrix shown in Table 1. The confusion matrix shows a 85.49% of correctly classified data (the diagonal terms).

A commonly used statistical measure to evaluate the agreement of categorical data is the kappa coefficient [Cohen60]. The advantage of this measure is that it takes the agreement occurring by chance into account. It is commonly considered that a substantial agreement is achieved when the obtained kappa values are greater than 0.6. In our experiments (Table 1) we obtained a kappa value of 0.69.

We should also mention that there were other order moment combinations that resulted in similar values. In total, there were 30 combinations with kappa greater than 0.6. Moreover, the single order moment with better discrimination was the number 2, with a kappa value of 0.63. However, when combining more that one moment orders, we found that orders 3, 11, and 12 appeared in the top five set of combinations.

Conclusion

We have shown in this paper that Zernike moments are useful to describe the mass shape for mass diagnosis purposes. In combination with a level set approach based on grey level instead of gradient, the Zernike moments effectively diagnose 49 of the 57 ROIs that compose our database. Obviously, better results are expected when taking other features into account, like grey-level information for describing the optical density of the mass, or features related to the abruptness of the margin.

Table 1

		Automatic estimation	
		No cancer	Cancer
Manual Classification	No cancer	33	4
	Cancer	4	16